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To b(ias) or not to b(ias)? This is the question

How often would you bias an inferential model? Given the propensity of instruments to go off calibration, "never" is not a valid answer. "Every day upon receiving lab information" is an equally bad answer, which means: I don't trust this inference at all, and every day I have to tell it what value it should be calculating. This last approach has been the prevailing one, although engineers who have some faith in their models have softened it with filtering techniques, for example:

- If that is a first-time deviation in that direction apply a bias of 10% of the deviation from lab data.
- For a second-time deviation bias 30% of the difference.
- For a third-time deviation bias 80% of the difference.

Are those filters reasonable? Yes and no. They take care of lab repeatability issues but not of dynamic differences between lab and inference. Lab sample points are way downstream of the inference input measurements, and there is an hour or two of transport delay between the two. Furthermore, the exact lab sampling time is difficult to ascertain. To be more realistic, the filtering logic should also look at the inference trend during the hours before and taking to determine the lab deviation.

Even then, biasing an inference model without first understanding the reason for error would not improve the inferential reliability. If the inference methodology is solid, then the most frequent cause of inferential errors are erroneous instrument readings, and only identifying and repairing culprit measurements could improve the reliability.

In the first instance inferential inputs are (or should be) validated by simple tests. My preference calls for:

- Check against low and high limits, if violated apply the last known good value. Do not let the value go to the limit unless that was the last good measured value. High and low limits are determined not by the instrument range but by process considerations.
- Limit the rate-of-change. The permitted rate-of-change is again determined from process considerations.
- Check for frozen values.
- And, of course, check against "bad value," which usually means no successful measurement took place.

When an input is suspect, the option is to either continue the inference using the last known good value, or to abort the calculation, and that is an engineering judgment depending on the influence of that input on the calculation reliability.

But validation tests, important as they are, only provide an initial stop-gap measure. We still have to worry about:

- Flow meters leads plugging up, flow orifices plugging or corroding
- Thermocouples drifting
- Pressure leads that plug or references drift
- Level floats that freeze or stick
- And the occasional self-inflicted problem: incorrect high and low limit tests, which yield an incorrect "last good value."

Is there an easy way to detect instrument problems? I normally historize many trends, not only of measurements but also of certain calculations to facilitate such detection.

- The first, and obvious, trend each of the inputs and their "last good value." Hopefully there are only transient insignificant differences between them.
- Equipment temperature profiles, where temperature patterns are known. Pressure compensation of the temperatures usually helps.
- Mass balances around the unit and all possible pieces of equipment
- Heat balance where possible.

What if after going through the effort, you still cannot explain a lab–inference deviation? I had a problem of that nature. The operation shifted after turnaround, but there was no evidence of erroneous measurements. We accepted that the model had drifted, except changing biases did not make the model reliable We asked for blowing each one of the orifice leads, then calibrating all orifice meters in the unit. Perhaps a desperate remedy but it did solve the problem and the inference immediately started trending against the lab again.

I would like to relay another inferential biasing war story. We are trained to treat lab tests with reverence but labs do have imperfections, often having to do with not the test itself but with sample-taking procedure. In that location lab values that were different from inferences would persist for several days, then shift, hold again for several days, etc. The pattern was not related to feedstocks or operational modes, and the operators became confused. Their inclination was to ignore the inferences, making operating changes to bring products into specifications, only to find out that they are off specifications again. Such a scenario takes time to comprehend because of operator discontinuity: One operator makes the changes but another one gets the next lab result. An analysis of many history trends revealed that it was not simply a problem of disagreement but more like several days delay between inference and lab. That was traced down to sample lines that were often not being flushed before sampling, and the problem was quickly corrected through personnel training.

To b(ias) or not to b(ias)? Bias if you wish, but not frequently and not without understanding the reason for biasing. If an orifice meter is corroded or a temperature point drifted, instrument errors of such nature can only be compensated by biasing. If you resort to mechanical formula-based biasing—that would surely be counterproductive. **HP**

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